

Active power output optimization for wind farms and thermal units by minimizing the operating cost and emissions

Nazha Cherkaoui, Abdelaziz Belfqih, Faissal El Mariami, Jamal Boukherouaa, Abdelmajid Berdai

Laboratory of Electrical Systems and Energy, National Higher School of Electricity and Mechanics (ENSEM), Morocco

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ABSTRACT

In recent years, many works have been done in order to discuss economic dispatch in which wind farms are installed in electrical grids in addition to conventional power plants. Nevertheless, the emissions caused by fossil fuels have not been considered in most of the studies done before. In fact, thermal power plants produce important quantities of emissions for instance, carbon dioxide (CO₂) and sulphur dioxide (SO₂) that are harmful to the environment. This paper presents an optimization algorithm with the objective to minimize the emission levels and the production cost. A comparison of the results obtained with different optimization methods leads us to opt for the grey wolf optimizer technique (GWO) to use for solving the proposed objective function. First, the method used to estimate the wind power of a plant is presented. Second, the economic dispatch models for wind and thermal generators are presented followed by the emission dispatch model for the thermal units. Then, the proposed objective function is formulated. Finally, the simulation results obtained by applying the GWO and other known optimization techniques are analysed and compared.

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Corresponding Author:

Nazha Cherkaoui,
Laboratory of Electrical Systems and Energy,
National Higher School of Electricity and Mechanics,
El Jadida Road, km 7, Casablanca, Morocco.
Email: nazha.cherkaoui@ensem.ac.ma

1. INTRODUCTION

Recently, the integration of the wind energy into electrical grids has increased significantly because it is clean and cheap in comparison to conventional energy sources. Therefore, in case of integration of wind farms (WF) with an existing grid with conventional sources, it is necessary to take also into account the wind power plants (WPP) in the economic dispatch (ED). In literature, many works have been done in order to discuss diverse methods of economic dispatch in which WFs are integrated into power systems.

In fact, in [1], an economic dispatch for combined wind thermal systems is realized using flower pollination algorithm (FPA). Besides, the authors in [2], present a new approach for ED problems in which WFs are installed in the network using particle swarm optimization (PSO) technique. Also, the authors in [3], discuss an economic load dispatch (ELD) in which solar and wind units are included in addition to thermal units. To resolve the ELD, the firefly algorithm optimization technique is used.

Nevertheless, although the fact that the wind energy is clean, the thermal power sources are considered as pollution sources. As a result, even the emissions have to be taken into account during the planning stage. In this paper, we propose an objective function that allows getting the optimal real power generation of the units which consist of thermal generators and WPPs. The proposed objective function aims to reduce both the production cost and emissions simultaneously. In this work, the potential power of a wind farm is considered as a constraint of the proposed objective function so that to not exceed the available wind power. The grey wolf optimizer (GWO) method is utilized in order to solve the proposed optimization algorithm.

This paper is organized as follows: first, the probability density function (pdf) of the weibull distribution is presented followed by the method used to estimate the wind power of a site. Second, the economic dispatch model for thermal conventional and wind units is described. Third, the emission dispatch model for thermal units is presented. Then, the proposed objective function is formulated. Finally, the case study and the simulation results are given.

2. WIND POWER ESTIMATION

The probability density function (pdf) of the weibull distribution is used to estimate the wind speed in any place. The probability density function $f_v(v)$ of the wind speed is expressed as follows [4]:

$$f_v(v) = \left(\frac{k}{c}\right) \left(\frac{v}{c}\right)^{(k-1)} e^{-\left(\frac{v}{c}\right)^k}, \quad 0 < v < \infty \quad (1)$$

where:

c : is the scale parameter

k : is the shape parameter

v : is the wind speed

The method cited in [5] is used for modelling the wind generator curve, as it is shown in Figure 1. This method is chosen because it is considered to be the most simplified method to simulate the power output of a wind generator [6]. The power provided by a wind turbine can be represented as [5]:

$$w = \begin{cases} 0 & v < v_c, v > v_f \\ w_r \frac{v-v_c}{v_r-v_c} & v_c < v < v_r \\ w_r & v_r \leq v \leq v_f \end{cases} \quad (2)$$

where:

v_c : is the cut-in wind speed of the wind turbine

v_f : is the cut-off wind speed of the wind turbine

v_r : is the rated wind speed of the wind turbine

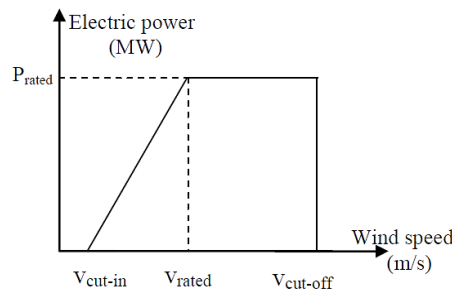


Figure 1. Power curve of a wind turbine [7]

The transformation of the probability distribution function pdf of the wind speed to the wind power can be expressed as follows [4]:

$$f_w(w) = \begin{cases} 1 - e^{-\left(\frac{v_c}{c}\right)^k} + e^{-\left(\frac{v_f}{c}\right)^k} & v < v_c, v > v_f \\ \frac{klv_c}{w_r c} \left(\frac{(1+\rho l)v_c}{c}\right)^{(k-1)} e^{-\left(\frac{(1+\rho l)v_c}{c}\right)^k} & v_c < v < v_r \\ -e^{-\left(\frac{v_r}{c}\right)^k} - e^{-\left(\frac{v_f}{c}\right)^k} & v_r \leq v \leq v_f \end{cases} \quad (3)$$

where:

$$\rho = \frac{w}{w_r} \text{ and } l = \frac{v_r - v_c}{v_c}$$

3. WIND POWER POTENTIAL OF A SITE

The wind power potential is given by [8]:

$$P(v) = \frac{1}{2} \rho \Gamma \left(1 + \frac{3}{k} \right) c^3 A \quad (4)$$

where:

A : Swept area of the rotor blades in m²

ρ : Air density (kg/m³) and is calculated as follows:

$$\rho = \rho_0 - 1.194 \times 10^{-4} \times H_m \quad (5)$$

with: $\rho_0 = 1.225 \text{ kg/m}^3$ is the air density value at sea level and H_m is the site elevation in m.

In this work, it is considered that H_m is equal to 343m.

Γ : gamma function

The standard gamma function is expressed by [9]:

$$\Gamma(x) = \int_0^{\infty} t^{x-1} \exp(-t) dt \quad (6)$$

4. ECONOMIC DISPATCH

The goal of the economic dispatch is to minimize the operating cost of generators contributing to provide the load demand. In this study, the valve point effect is taken into account in the economic dispatch. Hence, the operating cost of each conventional generator can be given by the following [10]:

$$C_i = a_i p_i^2 + b_i p_i + c_i + |e_i \sin(f_i(p_i^{\min} - p_i))| \quad (7)$$

where:

p_i : is the generation output of generator i

a_i, b_i, c_i : are the cost coefficients of generator i

e_i and f_i : are the cost coefficients of generator i reflecting valve point effects

The operating cost of the WPP is the sum of three components which are the direct cost, the penalty cost and the reserve cost. These three costs are explained in detail below. The system operator must pay a wind power generation cost C_{wi} to the wind producer which may not exist if the wind power plants are owned by the power operator [4].

$$C_{wi} = d_i w_i \quad (8)$$

where:

w_i : is the scheduled wind power from the wind power generator i

d_i : is the direct cost coefficient of the wind power generator i

If the scheduling of the wind power is less than it would be due to an underestimation of the available wind power, a penalty cost C_{pi} will appear that can be expressed as [4]:

$$C_{pi} = k_{pi} \int_{w_i}^{w_{ri}} (w - w_i) f_w(w) dw \quad (9)$$

where:

k_{pi} : is the penalty cost coefficient for the wind power generator i

$f_w(w)$: is the weibull distribution function for wind power

w_{ri} : is the rated wind power from the wind power generator i

The penalty cost may be equal to zero if the wind farm is owned by the power system. If the scheduling of the wind power is more than it would be due to an overestimation of the available wind power, a reserve cost C_{ri} will appear that can be given by [4]:

$$C_{r_i} = k_{r_i} \int_0^{w_i} (w_i - w) f_w(w) dw \quad (10)$$

where:

k_{r_i} : is the reserve cost coefficient of the wind power generator i

The total operating cost is expressed as follows:

$$C(X) = \sum_{i=1}^{n1} C_i + \sum_{i=1}^{n2} C_{w_i} + \sum_{i=1}^{n2} C_{p_i} + \sum_{i=1}^{n2} C_{r_i} \quad (11)$$

where:

X : the position of each particle having the dimension ($n=n1+n2$)

n1 : the number of the conventional generators

n2 : the number of wind power generators

5. EMISSION DISPATCH

The emission dispatch aims to allocate the optimal power outputs for various generator units with the objective to minimize the emissions. In this study, the emission function is represented by the quadratic function [11]:

$$E(X) = \sum_{i=1}^{n1} \alpha_i + \beta_i p_i + \gamma_i p_i^2 \quad (12)$$

where:

$\alpha_i, \beta_i, \gamma_i$: The emission coefficients of generator i

6. PROBLEM FORMULATION

In this work, the objective function aims to find the optimal allocation of power output from a combination of conventional generators and wind power plants by minimizing both the operating cost and the emissions. The proposed objective function is expressed as follows:

$$F(X) = w_1 C(X) + w_2 h_T E(X) \quad (13)$$

where:

w_1, w_2 : are weight's factors, where w_1 and $w_2 \geq 0$ and $w_1 + w_2 = 1$ [12]

h_T : is the total price in penalty factor PPF in \$/kg

The total PPF is expressed as the summation of PPF of thermal units [13]:

$$h_T = \sum_{i=1}^{n1} h_i \quad (14)$$

where:

h_i : is the price penalty factor of the generator i

In this paper, we use the equation below to calculate the PPF of the i-th generator because it was proved that the min/max PPF is better than other PPF types [13]:

$$h_i = \frac{C_i(p_i^{\min})}{E(p_i^{\max})} \quad (15)$$

The objective function proposed in (13) is subjected to the following constraints:

– Operating limits of the conventional and wind power generators:

$$p_i^{\min} \leq p_i \leq p_i^{\max} \quad (16)$$

$$0 \leq w_i \leq w_{r_i} \quad (17)$$

where:

p_i^{\max} : is the maximum limit of real power output of the conventional generator i

p_i^{\min} : is the minimum limit of real power output of the conventional generator i

w_{r_i} : is the rated wind power of the wind power generator i

– The estimated available wind power of the generator i which is obtained using (4):

$$0 \leq w_i \leq P(v) \quad (18)$$

– Power balance

The total power generated from the conventional and wind power generators should be equal to the total demand P_D plus the network losses P_L .

$$\sum_{i=1}^{n1} p_i + \sum_{i=1}^{n2} w_i = P_D + P_L \quad (19)$$

where the power losses are calculated using B matrix technique and is expressed by the [14]:

$$P_L = \sum_{i=1}^n \sum_{j=1}^n p_i B_{ij} p_j + \sum_{i=1}^n B_{0i} p_i + B_{00} \quad (20)$$

where B_{ij} , B_{0i} and B_{00} are coefficient of transmission loss. In this work, we use the B matrix cited in [15].

7. OPTIMIZATION ALGORITHMS

7.1. Grey wolf optimizer algorithm for solving the economic and emission dispatch

In this work, the GWO technique which is a new metaheuristic optimization method is proposed to solve the economic and emission dispatch problem due to its many advantages such as being simple in principle, having a fast seeking speed and being easy to realize [16]. Besides, in [17], twenty-nine test functions were used to benchmark the performance of the GWO in terms of exploitation, exploration, convergence and local optima avoidance. The results illustrated that GWO could provide highly competitive results compared to well known heuristics methods. The GWO method is invented by Seyedali et. al. in 2014 [17]. Grey wolves mostly live in a group called a pack. They are known by having a very strict social dominant hierarchy. In fact, in the hierarchy, the wolves within the pack are divided into alpha, beta, omega and delta. The first level of hierarchy of grey wolves is alpha. The alpha is responsible for making decisions about hunting and its decisions are dictated to the pack. Also, the alpha is considered to be the dominant, so his orders should be followed by the pack. The second level of hierarchy is beta. The beta wolves help the alphas in decision making. The delta wolves are in the third level of hierarchy. The delta have to obey to alpha and beta; however, they dominate the omega. In the lowest level, there are omega wolves that have to obey to all the other dominant wolves in the pack. In hunting, there are three main steps followed by a grey wolf: a) Finding, chasing, and approaching the prey. b) Encircling and harassing the prey until it stops moving. c) Attacking the prey.

In the grey wolf algorithm, it is considered that the alpha α is the fittest solution, while beta β and delta δ are considered respectively as the second and the third best solutions. The omega wolves follow the other three wolves. The equation to update the position of the pack is [17]:

$$\vec{D} = |\vec{C} \cdot \vec{X}_p - \vec{X}(t)| \quad (21)$$

$$\vec{X}(t+1) = \vec{X}_p - \vec{A} \cdot \vec{D} \quad (22)$$

where \vec{A} and \vec{C} are coefficient vectors, t is the current iteration, \vec{X}_p is the position vector of the prey, and \vec{X} is the position vector of the grey wolf. The vectors \vec{A} and \vec{C} are calculated using the [17]:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \quad (23)$$

$$\vec{C} = 2 \cdot \vec{r}_2 \quad (24)$$

where \vec{r}_1 and \vec{r}_2 are randoms vectors in $[0,1]$, and components of \vec{a} are linearly decreased from 2 to 0 during iterations. The position vector of the grey wolf is updated based on the positions vectors of the first three best solutions which are α , β and δ . In this regard, the following equations are used [17]:

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}|, \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}|, \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \quad (25)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha, \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta, \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \quad (26)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (27)$$

The steps for solving the economic and emission problem using the GWO algorithm are as follows:

Step 1. Generate randomly the grey wolf position of each search agent x_i^k .

Step 2. Evaluate the objective function for each search agent (13).

Step 3. Initialize \vec{X}_α , \vec{X}_β and \vec{X}_δ . \vec{X}_α is the position of the first best solution and \vec{X}_β and \vec{X}_δ are respectively the positions of the second and third best solutions.

Step 4. Update the position of each search agent (23), (24), (25), (26), and (27).

Step 5. Check that the constraints are satisfied (16), (17) and (18).

Step 6. Evaluate the objective function of each search agent (13).

Step 7. Update \vec{X}_α , \vec{X}_β and \vec{X}_δ .

Step 8. If the maximum iteration is not reached, return to step4. Otherwise, stop the algorithm.

7.2. Particle swarm optimization technique (PSO)

The particle swarm optimisation (PSO) technique is a metaheuristic algorithm invented by Kennedy and Eberhart in 1995 [18]. In this method, the initialization of a group of particles is done in a random manner in the d-dimensional search space, where d is the size of the decision variables in the optimization problem. To each i-th particle a position vector x_i , a velocity vector v_i and a position $Pbest_i$ are associated. The particles exchange effectively information during an iterative process so that to find the optimal solution. In each iteration, the PSO algorithm searches for the optimal solution by updating the velocity (28) and the position (29) of each i-th particle taking into consideration its previous best position $Pbest_i$ and the best position of the group $gbest$. At each iteration k, the equations allowing to update the velocity and the position of each particle are given by [19].

$$v_i^{k+1} = w v_i^k + c_1 r_1 (Pbest_i^k - x_i^k) + c_2 r_2 (gbest^k - x_i^k) \quad (28)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (29)$$

where:

r_1 and r_2 : Uniformly distributed random numbers in the range $[0, 1]$.

w : Inertia weight.

c_1 and c_2 : Acceleration coefficients.

The following equation is used to calculate the inertia weight [19]:

$$w^k = w_{\max} - \frac{w_{\max} - w_{\min}}{k_{\max}} \times k \quad (30)$$

where:

k : the current iteration.

k_{\max} : the maximum number of iterations.

w_{\min} and w_{\max} : are the lower and the upper bounds of the inertia weighting factors, respectively.

7.3. Bat algorithm (BA)

Bat algorithm (BA) is a metaheuristic optimization algorithm invented in 2010 by Yang [20]. In this optimization method, the echolocation behaviour of bats is used [20]. In order to look for prey, bat fly

randomly with a velocity v_i and a position x_i with a varying loudness A and frequency f . The equations below are used to update the positions of the bats [21]:

$$f_i^{(t)} = f_{\min} + (f_{\max} - f_{\min}) * u(0,1) \quad (31)$$

$$v_i^{(t+1)} = v_i^{(t)} + (x_i^{(t)} - x_{Gbest}) * f_i^{(t)} \quad (32)$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \quad (33)$$

where:

$u(0,1)$: is a uniform random number ranging from 0 to 1

x_{Gbest} : the best solution found by the swarm

A random walk is used for a local search and is expressed by [21]:

$$x_i^{(t)} = x_{Gbest} + \varphi A_i^{(t)} N(0, \sigma) \quad (34)$$

where:

φ : is a scaling factor allowing to limit the step size of the random walk

A_i : is the loudness

$N(0, \sigma)$: is a normal random number with a standard deviation σ and a mean equal to zero

when the bats are near their target, they decrease the loudness A_i and increase the pulse rate r_i . This can be expressed by [21]:

$$A_i^{(t+1)} = \alpha A_i^{(t)} \quad (35)$$

$$r_i^{(t+1)} = r_i^{(0)}(1 - \exp(-\gamma t)) \quad (36)$$

where α and γ are constants.

7.4. Gravitational search algorithm (GSA)

The GSA is a heuristic optimization algorithm invented in 2009 by Rashedi et al. [22]. GSA technique is based on the law gravity and motion. In this method, agents are considered as objects and their masses are used in order to measure their performance. The position of i -th agent is defined by [23]:

$$X_i = (x_i, \dots, x_i^d, \dots, x_i^n), i = 1, 2, \dots, m \quad (37)$$

where:

x_i^d : is the position of i th mass in the d th dimension

n : is the dimension of the search space

At a specific time t , the force acting from mass j to mass i is given by the following [23]:

$$F_{ij}^d(t) = G(t) \frac{M_i(t) x M_j(t)}{R_{ij}(t) + \varepsilon} (x_j^d(t) - x_i^d(t)) \quad (38)$$

where:

M_i and M_j : are the masses of the objects i and j

R_{ij} : is the euclidean distance between the objects i and j

ε : is a small constant

G : is the gravitational constant at time t

First G is initialized with G_0 and then will decrease according to the time using in [23]:

$$G(t) = G_0 e^{-\alpha \frac{t}{T}} \quad (39)$$

where α is a descending coefficient, t is the current iteration and T is the maximum number of iterations.

The total force acting on the agent i in the d dimension is given by the following in [23]:

$$F_i^d(t) = \sum_{j=1, i \neq j}^m \text{rand}_j F_{ij}^d(t) \quad (40)$$

where rand_j is a random number in the interval $[0 \ 1]$.

The acceleration at time t of the agent i in the d dimension is expressed by [23]:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \quad (41)$$

The velocity and the position of each agent is updated according to the [23]:

$$v_i^d(t+1) = \text{rand}_i \times v_i^d(t) + a_i^d(t) \quad (42)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \quad (43)$$

where:

rand_i : is a random number from the interval $[0,1]$

v_i^d : is the velocity of the agent i in the d dimension

x_i^d : is the position of the agent i in the d dimension

8. SIMULATION AND RESULTS

In order to test the proposed optimisation algorithm, three different cases are simulated using the IEEE 30 bus system. The test system is constituted of five conventional plants and one wind farm. The five conventional thermal plants are at buses 1, 2, 22, 27 and 23. While, the WF is at bus 13. Table 1 illustrates the cost and emission coefficients and the maximum and minimum power output of each conventional generator in the test system [13].

Table 1. Thermal generators data

Units	Bus	P_{\max} (MW)	P_{\min} (MW)	Cost coefficients				Emission coefficients			
				a (\$/ $MW^2 \cdot h$)	b (\$/ $MW \cdot h$)	c (\$/h)	e (\$/ h)	f (rad/ MW)	γ (kg/ $MW^2 \cdot h$)	β (kg/ $MW \cdot h$)	α (kg/h)
1	1	200	50	0	2	0.00375	15	0.063	0.0126	-0.9	22.983
2	2	80	20	0	1.7	0.0175	14	0.084	0.02	-0.1	25.313
3	22	50	15	0	1	0.0625	12	0.15	0.027	-0.01	25.505
4	27	35	10	0	3.25	0.00834	10	0.20	0.0291	-0.005	24.9
5	23	30	10	0	3	0.025	10	0.25	0.029	-0.004	24.7

The wind farm utilized in this paper has a capacity of 120 MW. It is considered that the wind turbine technology installed in the WPP is V90/3000 (Vestas) [24]. Therefore, the rated power and the swept area of the rotor blades of the wind turbines installed in the WPP are respectively 3 MW and 6361.7 m². Besides, Table 2 shows the values of the wind farm production limits (WF_{\min} and WF_{\max}), the direct cost coefficient, the reserve cost coefficient and the penalty cost coefficient of the WF in the test system.

Table 2. Wind farms data

WF	Bus	WF_{\min} (MW)	WF_{\max} (MW)	k_r (\$/MW.h)	k_p (\$/MW.h)	d (\$/MW.h)
1	13	0	120	1	1	1.25

In the three cases, the load system is considered to be equal to 300 MW. Also, the value of the shape k and scale parameter c are considered to be respectively equal to 2.14 and 7.29 of tangier region cited in [25].

- Case 1: the weight's factors are considered to be $w_1=1$ and $w_2=0$.
- Case 2: the weight's factors are considered to be $w_1=0$ and $w_2=1$.
- Case 3: the weight's factors are considered to be $w_1=0,5$ and $w_2=0.5$.

In each case, 10 runs are done using the GWO and three other metaheuristic optimization algorithms: the PSO, the BA and the GSA which are used in the purpose of comparison. The optimization parameters are shown in Table 3. In each case, the average values of the active power outputs, the losses, the total operating cost and the emissions obtained in the ten runs for each optimization method are

calculated and reported in Table 4. As we can notice from Table 4, when the only objective to minimize is the total cost, the GWO method attained better results than PSO, BA and GSA. In fact, the GWO method permits achieving the lowest average value of the total operating cost.

In the second case, when the only objective to minimize is the emissions, the GWO performs better than the other optimization methods by producing the best results. Indeed, the average values of the emissions obtained using the GWO is 280.6020 kg/h, while the average values obtained with PSO, BA and GSA are respectively 280.7096 kg/h, 301.0234 kg/h and 299.9055 kg/h. In the third case, when the objective is to reduce both the operating cost and the emissions, the GWO permits getting the lowest value of the operating cost in comparison to PSO, BA and GSA. Regarding the emissions, the PSO attained the best results. Nevertheless, the GWO permits getting better results than the BA and the GSA. In fact, the average values of the emissions obtained with the GWO, BA, and GSA are respectively 293.9747 kg/h, 314.7205 kg/h and 301.7588 kg/h.

According to the simulation results, the maximal real power provided from the WF is 72.5881 MW which represents the wind power potential of the site. Therefore, considering the wind power potential of a site as a constraint of the multi objective function proposed in this paper, permits not exceeding the available wind power. In addition, the GWO method can be used to solve such optimization problems due to the fact that it allows getting better results by reducing both the operating cost and the emission levels simultaneously in comparison to some known optimization algorithms, as we can notice from the simulation results.

Table 3. Optimization parameters

Algorithm	Parameter	Value
GWO	Population size	50
	Maximum number of iterations	300
PSO	Inertia weight [w_{min} , w_{max}]	[0,4 0,9]
	Acceleration coefficients $c1$ et $c2$	2.05
BA	Population size	50
	Maximum number of iterations	300
	Minimal frequency f_{min}	0
	Maximal frequency f_{max}	10
	Initial loudness $A0$	0.8
	Initial pulse rate	0.2
	α	0.5
GSA	γ	0.99
	Population size	50
	Maximum number of iterations	300
	G0	1
	Alpha	20
	Population size	50
	Maximum number of iterations	300

Table 4. Simulation results in case 1, 2 and 3

		P_{G1} (MW)	P_{G2} (MW)	P_{G3} (MW)	P_{G4} (MW)	P_{G5} (MW)	WF (MW)	Losses (MW)	Cost (\$/h)	Emissions (kg/h)
GWO	Case 1	97.2827	68.1024	49.9836	15.4791	11.5028	71.3663	13.7126	591.7045	332.2490
	Case 2	93.9350	49.8919	35.1905	30.9843	29.2403	72.5875	11.8268	652.9325	280.6020
	Case 3	98.2988	56.9400	43.6185	22.2048	19.1431	72.5801	12.7876	602.5224	293.9747
PSO	Case 1	104.2088	57.5724	40.2388	20.8039	21.2983	70.2856	14.4070	601.1491	301.6389
	Case 2	94.0388	49.9212	35.4454	31.1781	28.6784	72.5881	11.8499	652.6833	280.7096
	Case 3	98.9233	57.1827	36.7936	24.6916	22.7341	72.5881	12.9147	609.2529	286.4942
BA	Case 1	113.7615	64.6990	46.7983	19.9877	18.7758	54.7075	18.7311	624.2498	372.3040
	Case 2	98.7950	54.1547	38.7475	31.0350	27.0902	62.7787	12.6011	642.6974	301.0234
	Case 3	96.4998	63.3013	45.1112	25.2148	19.7692	62.2645	12.1657	616.3462	314.7205
GSA	Case 1	79.0054	77.4359	49.9673	14.3471	22.1248	67.4405	10.3942	604.1017	342.4549
	Case 2	98.2276	59.1196	33.8145	28.0358	21.7640	72.0832	13.0878	646.3965	299.9055
	Case 3	88.3872	60.8938	43.0503	22.0044	24.2149	72.4343	10.9607	626.9505	301.7588

9. CONCLUSION

In this paper, we present an optimization algorithm based on grey wolf optimizer (GWO). The proposed algorithm allows obtaining the active power output of thermal and wind power plants installed

in the grid with the objective to reduce the cost production and emission levels simultaneously. Three different cases using the GWO, PSO, BA and GSA are analysed and compared. The proposed optimization method allows minimizing significantly the emissions and the operating cost as illustrated in the simulation results.

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BIOGRAPHIES OF AUTHORS

Nazha Cherkaoui is a Ph.D. student at the National Higher School of Electricity and Mechanics (University Hassan II of Casablanca - Morocco). Her research interests include renewable energies and power systems.



Abdelaziz Belfqih is a professor at the National Higher School of Electricity and Mechanics (University Hassan II of Casablanca - Morocco). PhD, Engineer and holder of the University Habilitation searches (HDR). Member of the research team "Electrical Networks and Static Converters". Teacher researcher currently working on stability of electricity network and smart grids



Faissal El Mariami is a professor at the Superior National Higher School of Electricity and Mechanics (University Hassan II of Casablanca - Morocco). PhD, Engineer and holder of the University Habilitation searches (HDR). Member of the research team "Electrical Networks and Static Converters". Teacher researcher currently working on stability of the electricity network and smart grids.



Jamal Boukherouaa is a professor at the National Higher School of Electricity and Mechanics (University Hassan II of Casablanca Morocco). PhD, Engineer and holder of the University Habilitation searches (HDR). Member of the research team "Electrical Networks and Static Converters". Teacher researcher currently working on high frequency static converters.



Abdelmajid Berdai holds a doctorate in engineering. He is currently Associate Professor and Chair of the Department of electrical engineering in the National School of Electricity and Mechanics (University Hassan II of Casablanca Morocco). Member of the research team "Electrical Networks and Static Converters". His research interests include Dynamic Simulation of Electric Machinery, Simulation and optimization of renewable energy systems, the use of quality power conversion for monitoring of electromechanical equipment state, estimation of modes and diagnosis of induction motors based on the quality of energy conversion.